Paid Music Streaming: What Drives Customers' Choice?

Vafa Saboori-Deilami*
Dominican University of California, San Rafael, California, USA

Chang Seob Yeo
Dominican University of California, San Rafael, California, USA

This study investigates factors that determine the choice of consumers in selecting online music streaming services, and factors that affect the customer's choice to opt for a paid music streaming service. Using multiple theoretical lenses, this study proposes a conceptual model. This study validates the hypotheses of the conceptual model by analyzing empirical data. This data has been collected from more than 300 subscribers to paid music streaming services. Implications for consumers and producers of online music streaming services are discussed.

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* Corresponding Author. E-mail address: vafa.saboori@dominican.edu

I. INTRODUCTION

1.1. Background

Music related industries are experiencing a new technological innovation that is disrupting their revenue model. Everyday more and more customers are subscribing to free or paid online music streaming services. Streaming services enable customers to access a huge library of music for free or for a fixed monthly payment (Datta et al., 2017).

According to latest Global Music Industry Report (IFPI, 2018), in 2017 streaming music was the largest segment of global recorded music industry revenue. While the revenue from ownership model, i.e. physical music media and digital music (excluding streaming), has declined over the last five years, the revenue from music streaming has increased from $1.0 Billion in 2012 to $6.6 Billion in 2017 (IFPI, 2018). As evident in Figure 1, music streaming revenue has increased with the average rate of 46.1% between 2013 and 2017.

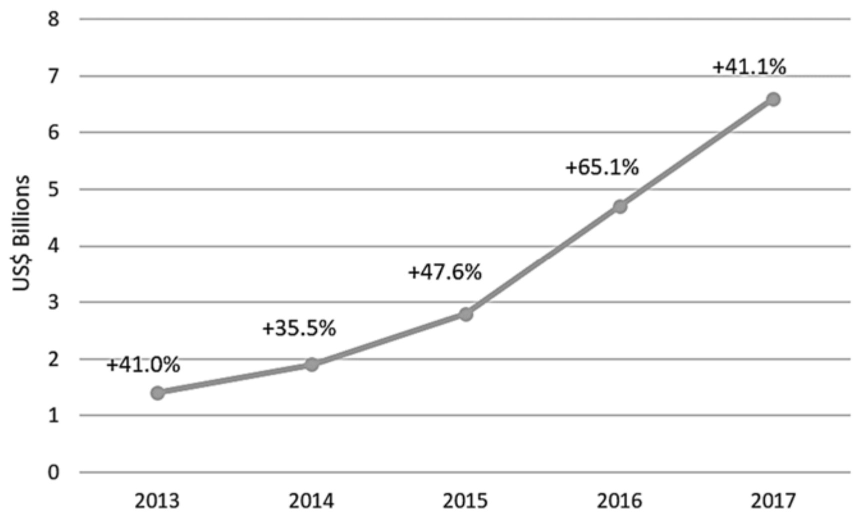

FIGURE 1. GROWTH OF STREAMING REVENUE (SOURCE: IFPI 2018)

1.2. Literature Gap and Theoretical Contribution

This growing trend for the adaptation of music streaming has provoked a s stream of research among scholars to explore different aspects of this phenomenon (Datta et al., 2017). For instance Wlömert and Papies (2016) found that free music streaming with radio-like advertisements cannibalizes the demand for paid subscription channels. Other researchers found that streaming music will replace ownership models, i.e. physical media, and downloadable music. More specifically they argued that free streaming music services increase the likelihood of illegally downloading music among users (Aguiar and Waldfogel, 2015).

However, streaming music literature lacks studies that identify factors that lead customers to convert from free streaming to paid subscriptions. The general concept of digital music and music piracy has been studied in the disruptive innovation and technology acceptance model frameworks (Ariss and Saboori, 2012; Saboori and Callaway, 2012; Callaway, 2010; Anthony and Christensen, 2006). This study contributes to the literature on digital music by extending its context to the streaming segment. Through investigating the reasons that push music consumers to select paid streaming subscription over free, ad-supported service, this study contributes to this literature.

Most studies have mainly used one specific theoretical perspective to study the notion of music streaming and digital music in general (Datta et al., 2017; Sanitnarathorn, 2018; Aguiar and Waldfogel, 2015; Plowman and Goode, 2009). Literature on music streaming and digital music suffers from lack of a multi-theoretical approach. This study fills this gap by employing multiple theoretical frameworks to synthesize a conceptual model that explains why and how music consumers convert from free and ad-supported streaming services to paid subscription models of music streaming.

To be specific, this study uses technology acceptance model (Davis, 1989), theory of planned behavior (Ajzen, 1991), the theoretical framework developed by Cronin et al. (2000) on effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments, and finally the framework proposed by

Dodds et al. (1991) on effects of price, brand, and store information on buyers' product evaluations.

This study also contributes to the literature from an empirical standpoint. Previous studies in the field of music streaming mainly either focused on the revenue models and economic viability of such services (Flynn, 2016; Wlömert and Papies, 2016; Naveed et al., 2017), or investigated the customer experience and behavior from different angles (Borja et al., 2015; Morris and Powers, 2015). The extant literature suffers from the lack of studies that categorize the factors leading to consumer's decision to opt for paid streaming service. This study contributes to the literature by filling this gap.

This study focuses on three paid music streaming services, Apple Music, Spotify, and Pandora. The reason behind selecting these three services is that they are the most popular services in the United States. According to a recent report (Statista, 2018) the subscribers of these three services together constitute more than half of all the subscribers to streaming services in the United States.

The remainder of this paper is organized as follows: In the next section, a review of the literature used in developing the conceptual model will be presented. Next in the theory development part, the conceptual model, construct definitions, and hypotheses development will be presented. Subsequently, in the research method section, the process of sample selection, and data collection, as well as instrument development, and statistical analysis would be introduced. Finally, in the discussion and conclusion section, results of statistical analysis will be explained, and implication of these results for practitioners and scholars will be discussed.

II. LITERATURE REVIEW

2.1. Theory of Planned Behavior

Theory of planned behavior (Ajzen, 1985, 1991) states that human behavior is a product of behavioral intentions. This theory posits that these intentions in turn are driven by human attitude towards the specific behavior. Theory of planned behavior also states that two other factors, subjective norm, and behavioral control, also influence the behavioral intention. Ajzen (1991, p.188) defines the attitude towards the behavior as "the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question". Attitude is formed through the evaluation of individual's beliefs about the outcomes of the behavior and the assessment of the appropriateness of those outcomes. In other words, the individual's attitude toward certain behavior could be measured as the product of perceived consequences for the individual and the level of desirability for those consequences.

According to Ajzen (1991, p.188), subjective norm surrounding the performance of the behavior are "the perceived social pressure to perform or not to perform the behavior". In other words, subjective norm is reflective of the individual's mindset towards whether people who are significant to him or her, believe that this specific behavior should or should not be performed. The more an individual is willing to comply with the opinion of the important referent, the higher the weight of their opinion. Therefore, total subjective norm is the product of individual's perception towards referent's judgment and the willingness of the individual to comply with referents' perceived belief.

Perceived behavioral control is the most pivotal concept in the theory of planned behavior. According to Ajzen (1991) this is what makes the theory of planned behavior different from the theory of reasoned action

(Fishbein and Ajzen, 1980). In the theory of reasoned action Fishbein and Ajzen (1980) argued that intentions are only driven by subjective norm and attitudes towards behavior. Ajzen (1991, p.183) defines perceived behavioral control as "people's perception of the ease or difficulty of performing the behavior of interest."

According to this theory, people perceive that they have different levels of control over their behaviors. These perceived controls vary on a range from behaviors that easily could be performed to behaviors that demand significant amounts of efforts and assets. Ajzen argues that in fact, there is an association between the actual behavioral control and behavior. However since measuring actual control incurs considerable difficulties, perceived behavioral control should be used as a proxy for assessing the actual control.

2.2. Technology Acceptance Model

Technology acceptance model (Davis, 1989) is one of the most widely used and empirically tested theoretical models for explaining the user behavior in different computer systems applications (Davis et al., 1989; Mathieson 1991; Szajna 1996; Hu et al., 1999; Koufaris, 2002). According to the technology acceptance model, users' attitudes towards the computer system affect their intention to use the system which in turn leads to the actual use of the computer system (Davis, 1989). Technology acceptance model proposes that when users are faced with a new technology, two factors influence their attitude and consequently their decision about the usage of the new technology. According to Davis (1989) these two factors are "perceived ease of use" and "perceived usefulness" of the new technology. Davis (1989, p.320) defines perceived ease of use as "the degree to which a person believes that using a particular system would be free from effort" and the perceived usefulness as "the degree to which a person believes that using a particular system would enhance his or her job performance".

Technology acceptance model has been repeatedly revised by scholars (Venkatesh and Davis, 2000; Venkatesh and Bala, 2008; Venkatesh at al., 2003). Venkatesh and Davis (2000) explained the reasons for users' perceived usefulness and ease of use in more details. Specifically they broke down the reasons to three time frames of before implementation, after implementation, and long after implementation. They argued that main foundations for creating perceptions towards usefulness of a computer system are the users' mental judgment of the alignment between essential objectives at work and the results of conducting the task related to one's job using the computer system. Results of their study showed that their findings are valid in voluntary and compulsory work environments.

Since customers of online music streaming services are in effect computer users, therefore, their behaviors, decisions, and reactions towards this new disruptive technology could be well explained by a behavioral information system theory like technology acceptance model. In this study we treat music streaming technology as new information systems introduced to users, and the consumers as computer users. By applying technology acceptance model to the context of this study, we develop and test a model that explains the intentions of users towards the use of music streaming services.

2.3. Effects of Quality and Value on Behavioral Intentions

Other streams of literature assessed the factors leading to behavioral intention from an objective point of view. In other words, instead of focusing on individual's psyche, they focused on specific characteristics of service that leads to specific behavioral intentions (Dodds et al., 1991; Cronin et al., 2000; Parasuraman et al., 2002; Lemon et al., 2016; Ranjan et al., 2016). According to these studies, behavioral intention is mainly driven by service quality, and this construct plays a pivotal role in these theories (Dodds et al., 1991; Cronin et al., 2000). Service quality is a popular construct among researchers and has been intensively studied (Parasuraman et al., 2002; Achrol et al., 2017; Sureshchandar et al., 2002; Parasuraman, 2010). Researchers agree on the notion that service quality measures the relative balance between customer expectations and service providers' performance (Cronin et al., 2000; Dodds et al., 1991). According to Lewis and Booms (1983) "Service quality is a measure of how well the service level delivered matches customer expectations. Delivering quality service means conforming to customer expectations on a consistent basis."

Another main factor that according to this stream of literature directly and indirectly leads to behavioral intention is service value (Cronin et al., 2000, Dodds et al., 1991). Service value is defined as "the consumer's' overall assessment of the utility of a product based on perceptions of what is received and what is given" (Zeithaml, 1988 p. 14). The indirect effect of service value on behavioral intention is through satisfaction which is defined as the assessment of an emotion which illustrates the extent to which the individual believes that the acquisition or utilization of a product or service arouses positive and pleasant emotions (Hill and Brierley, 2017; Hill and Alexander, 2017; Hunt, 1977, Rust and Oliver, 1994, Cronin et al., 2000). According to Cronin et al. (2000), service value in turn is affected by sacrifice. Sacrifice is essentially what is surrendered or paid to obtain a specific service (Cronin, 2000). Finally, according to Cronin (2000) service value and satisfaction, both driven by service quality, are also correlated. In other words, higher levels of service value leads to higher levels of satisfaction.

Behavioral intention has also been conceptualized as likelihood to buy (Dodds et al., 1991). Comparing different studies shows that the direct and indirect effect of perceived quality and perceived sacrifice with behavioral intention through perceived value, is present when the behavioral intention construct is conceptualized as the intention to perform a specific behavior i.e. purchase or likelihood to buy (Cronin et al., 2000, Dodds et al., 1991).

III. THEORY DEVELOPMENT

3.1. Conceptual Model

In this section, drawing on the technology acceptance model (Davis. 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008; Venkatesh at al., 2003), theory of planned behavior (Ajzen, 1985, 1991), and studies that link behavioral intention to quality and value of service (Cronin et al., 2000, Dodds et al., 1991), we propose a conceptual model for the study of customer behavior and attitudes towards music streaming. In this model we adapt "perceived sacrifice" and "perceived quality" from studies that propose an association between behavioral intention and quality and value of service (Cronin et al., 2000, Dodds et al., 1991). We then redefine these constructs in the context of this study. In our conceptual model, these two constructs are considered as antecedents of "perceived value". This construct has been adopted from Cronin et al. (2000) and Dodds et al., (1991) among other studies.

In this model we are addressing the non-consumption, i.e. subscription to free, ad-supported, streaming service, as the main market for the paid music streaming services e.g. Apple Music. Although streaming is the biggest segment of revenue in the recorded music industry (IFPI, 2018), one should note that a huge proportion of users of the streaming service are only using the free service. For instance Spotify has a total of 170 million active users, but only 75 million (44%) of them are using the paid subscription service (Welch, 2018). Numbers are much worse for Pandora with 71.4 million active users and only 6 million (8%) paid subscribers.

Perceived value also serves as the mediating variable in our model. This construct is adapted from the literature that suggest a relationship between behavioral intention and quality and value of service (Cronin et al., 2000, Dodds et al., 1991). In our conceptual model, perceived value on one hand, is the consequence of perceived quality and perceived sacrifice, and on the other hand is an antecedent for likelihood to subscribe. Finally we introduce subjective norm as the antecedent of perceived quality and likelihood to subscribe. This construct has been adapted from the revised technology acceptance model (Venkatesh and Davis, 2000; Venkatesh and Bala, 2008; Venkatesh at al., 2003). In the next section of this paper, detailed construct definitions will be provided. The proposed conceptual model is illustrated in Figure 2.

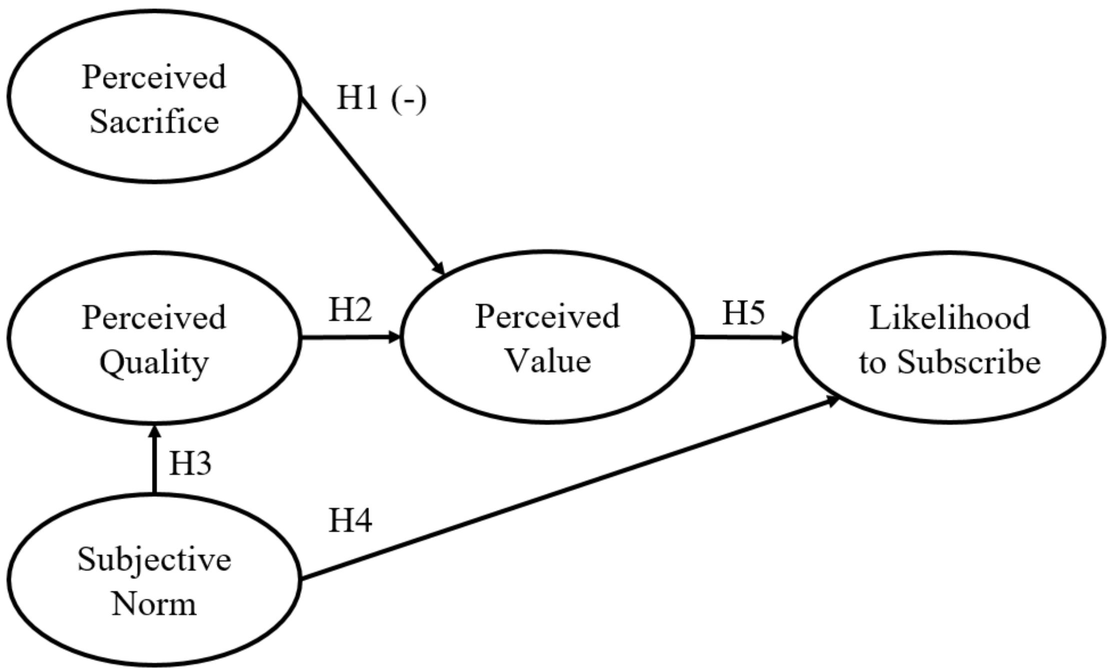

FIGURE 2. PROPOSED CONCEPTUAL MODEL

3.2. Construct Definition

Drawing on the work of Lovelock and Patterson (2015), Lemon and Verhoef (2016), Cronin et al. (2000), Dodds et al. (1991), and Ponte et al. (2015), this study defines perceived sacrifice in the context of music streaming as "what the music user believes that he or she should give up in order to be able to purchase a paid subscription service." This study considers perceived sacrifice as a multi-dimensional construct that cover monetary and non-monetary cost of being a paid subscriber of streaming services. Obviously monetary dimension includes the monthly subscription fee, and the non-monetary dimension includes time and effort spent for acquiring a specific streaming service.

Scholars have conceptualized quality from many different perspectives, however the performance based approach is the most comprehensive view (Parasuraman, 2010; Parasuraman et al., 2002; Getz and Page, 2016; Lemon and Verhoef, 2016). Building on this stream of literature, this study defines the perceived quality in the context of music streaming as "a measure of how well and consistent the characteristics of a specific music streaming service fits the expectations of the paid subscriber." In this definition, consistency and characteristics have the same importance. In other words, the ability of the paid streaming service to present characteristics that customer expects is only valuable if they remain consistent over time.

According to seminal works in the theory of technology acceptance model (Venkatesh et al., 2003) and theory of planned behavior (Ajzen, 1991, 2015) subjective norm is viewed as the social pressure on the individual to perform certain behavior. Drawing on this line of research, this study define subjective norm in the context of paid music streaming services. In order to do so, we first introduce the concept of influencer (Bakshy et al., 2011). Influencer which is a relatively new concept (De Veirman et al., 2017) refers to an individual who has a sizable follower base (specifically on social networks like twitter) in a particular niche, which they actively engage with. Drawing on this concept we define influencer as "an individual who has the power to shape the purchasing decision of music listener in choosing between paid streaming services". Based on this notion, this study defines subjective norm as "one's perception of whether the "influencers" that he or she praise, think that a specific paid music streaming service should be used."

The concept of perceived value has been studied from different angles (Lovelock and Patterson, 2015; Zeithaml, 1988; Lemon and Verhoef, 2016). Most of these studies consider the consumer central to their evaluations, and defined value as the general evaluation of utility by customer. Drawing on this line of research, this study defines the perceived value in the context of paid music streaming services as "the music consumers' overall assessment of the usefulness of a paid music streaming service according to what they receive and what they give."

The final construct, i.e. dependent variable, in our conceptual model is likelihood to subscribe. This study builds upon the works of Dodds et al. (1991), Schivinski and Dabrowski (2016), Ponte et al. (2015), and Chung and Koo (2015) to define this variable in the context of paid music streaming services. We define likelihood to subscribe as "individual's readiness to subscribe to a specific paid music streaming service". Based on the above definitions, in the next section, this study rationalize the relationships proposed in the conceptual model.

3.3. Hypotheses Development

The relationship between sacrifice and value has been stipulated as an adverse relationship (Monroe, 1990, Dodds et al, 1991; Cronin et al., 2000; Woodruff, 1997; Sirakaya-Turk et al., 2015). Sacrifice, in essence, is the perception of what needs to be given up in order to obtain the service. Whereas the value is basically the general evaluation of utility by customer. If the customer believes that the monetary and non-monetary cost of acquiring a streaming service is relatively high, the value of that service, i.e its relative utility will diminish in his or her view.

Conversely, the perception towards value involves a tradeoff between quality and sacrifice. This tradeoff results in a positive relationship between quality and value, as opposed to the negative relationship between sacrifice and value (Hauser and Urban, 1986; Kumar and Reinartz, 2016). Therefore this study posits that:

H1. *Individuals, who perceive higher degrees of sacrifice, will perceive lower degrees of value in subscribing to a specific paid music streaming service.*

H2. *Individuals, who perceive higher degrees of quality, will also perceive higher degrees of value in subscribing to a specific paid music streaming service.*

Technology acceptance model (Venkatesh and Davis, 2000; Venkatesh and Bala, 2008; Venkatesh et al., 2003) posits that when an individual perceives that important referents state that one should utilize a system, the individual internalizes the referents' idea in their belief system. In the context of this study, if a influencer suggests that a specific paid streaming service is useful, an individual follower might come to this conclusion that it actually is useful, and bears the characteristics that he or she needs, i.e. is high quality. Moreover, this internalization could as well lead to higher intentions to use the system. From another perspective, based on Raven's (2017) classification of power, the basis of this internalization process is expert power. In fact, the influencer sits in the position of expert and gains all related credibility. Therefore by endorsing a specific paid music streaming service, individual followers perceive that the service has their expected quality, and would be willing to purchase its subscription. Therefore this study posits:

H3. *Individuals who perceive higher degrees of subjective norm to subscribe to a specific paid music streaming service, will also perceive higher degrees of quality about that service.*

H4. *Individuals who perceive higher degrees of subjective norm to subscribe to a specific paid music streaming service, will demonstrate higher likelihood for subscribing to that service.*

Several researches have examined the relationship between perceived value and intention to purchase (Zeithaml, 1988; Lemon and Verhoef, 2016; Chiu et al., 2014). These studies argue that value has a direct positive effect on the intention to purchase. More importantly, this stream of literature states that perceived value serves as the mediator between quality and intention to purchase. In other words, although highest quality is always very appealing to customers, not all customers want to purchase the highest quality service. Rather, quality of a service is factored in its perceived value. A specific service might possess the highest quality, however if the customer does not have the budget to purchase it, its value will be perceived equal to a service with lower quality and more reasonable price. Therefore this study posits:

H5. *Individuals who perceive higher degrees of value in subscribing to a specific paid music streaming service, will demonstrate higher likelihood for subscribing to that service.*

IV. RESEARCH METHOD

4.1. Instrument Development, and Data Collection

Data were collected through Amazon Mechanical Turk (MTurk), which is a popular platform for data collection. Previous studies have noted its usefulness and reliability as a source to recruit participants from the general population (e.g., Buhrmester, Kwang, and Gosling 2011; Goodman, Cryder, and Cheema 2013; Paolacci, Chandler, and Ipeirotis 2010; Rand 2012). Goodman, Cryder, and Cheema (2013) suggested the use of screening/filtering function and considers demographic properness of participants of the study, with addressing the differences between participants recruited from MTurk and those from other sources (e.g., community members and students). Thus, those who only meet two preset conditions were able to participate and fill out the survey questionnaire. Screening variables are (1) incentive approval ratio (i.e., >89%) and (2) country in which they reside (i.e., United States). Also there were additional screening questions in the survey questionnaire. In exchange for their participation, a monetary compensation was granted. Total sample size was 330.

Participants were asked to make their subscription decision before answering main measurement questions. They were instructed to review the given information about three most popular music streaming services (i.e., Apple Music, Spotify, and Pandora) and also were encouraged visit the review website of each service to compare them in terms of pricing, best music quality, free version availability, etc. Then, they were asked whether they decided to subscribe to one of each services and which service they would subscribe to.

The measured constructs are perceived quality, perceived value, sacrifice, subjective, norm, and likelihood to subscribe. Table 1 provides descriptive statistics for the measurement scales.

TABLE 1. OBSERVED VARIABLE DESCRIPTIVE STATISTICS

	Mean	SD
SN	*5.424*	*1.4*
PERSAC1	*4.17*	*1.369*
PERSAC2	*5.23*	*1.244*
PERSAC3	*3.548*	*1.58*
PERSAC4	*3.182*	*1.707*
PQ1	*5.87*	*1.122*
PQ2	*5.727*	*1.177*
PQ3	*5.83*	*1.176*
PQ4	*6.2*	*1.063*
PQ5	*6.021*	*1.088*
PV1	*5.806*	*1.167*
PV2	*5.115*	*1.309*
PV3	*5.603*	*1.161*
PV4	*5.47*	*1.194*
LTS1	*5.582*	*1.434*
LTS2	*5.542*	*1.427*
LTS3	*5.433*	*1.488*
LTS4	*5.597*	*1.452*

Subjective norm was measured by an item adapted from Venkatesh and Davis (2000) indicating the level of perceived social pressure onto his or her subscription decision making. Measurement items of Perceived sacrifice were adapted from Cronin et al. (2000) which are capturing the level of perceived monetary as well as non-monetary efforts. Perceived quality, perceived value, and likelihood to subscribe were measured by items adapted from Dodds et al. (1991). For all of questions, 7-point

Likert scale was used. The actual questions included in the survey questionnaire, along with question/item scale, are provided in Appendix A.

4.2. Statistical Analysis and Results

To successfully complete the survey questionnaire, participants were asked to evaluate all three brands with answering questions before making their subscription decision. For the final dataset, participant's answers matched his/her final choice. In other words, if a participant selected Apple Music, his/her answers on Apple Music were used in data analysis. We use partial least square-based structural equation modeling (PLS-SEM) method to estimate both the latent variable scores and the paths shown in the proposed model (see Figure 2 above). PLS-SEM method is a very well-known and widely used method in marketing research (e.g., Hult et al. 2017). Through PLS-SEM, the measurement and structural models are analyzed simultaneously. This method uses iterative implementation of ordinary least squares estimation via the PLS-SEM algorithm (because the proposed model involves reflective measures, the consistent PLS-SEM algorithm was used with SmartPLS 3) to solve models. This way of estimation relaxes the multivariate normality assumption. Also, it is preferable to alternative conventional structural equation modeling (CB-SEM) method when the focus is on optimized prediction of a predicted variable, as it is of this study (e.g., Chin 1998, Hair et al. 2014). The subsequent sections report the results and key statistics for the measurement model (e.g., reliability and validity) and the structural model (e.g., model coefficients).

Table2 presents results for the measurement model including factor weights and loadings, and evidence of reliability and validity. All the loadings are between .67 and .80 (p value < .001). Both reliability measures (i.e., Cronbach's Alpha and Composite reliability) are greater than. /7 and AVEs are greater than 0.5. In sum, results show there are good convergent validity, discriminant validity, and reliability.

Table 3 provides the item loadings and cross-loadings. As shown in the table, all of items load most strongly on their own latent constructs.

Now we turn to the results for the structural model. Table4 provides path coefficients, standard deviation, T statistics, and p values. Perceived quality has the positive influence on perceived value (b = .632; p < .001) but perceived sacrifice was not predictive of perceived value (b = -.035; p = .614). The direction shows that perceived sacrifice negatively influences perceived value. It may be because music streaming service is pervasive and not totally innovative and also because market competition made the price difference is so subtle where customers would not use price point as a surrogate measure of quality. Perceived value shows its significant positive influence on likelihood to subscribe (b = .834; p < .001). Subjective norm significantly influences perceived quality (b = .444; p < .001) but does not have any significant influence on likelihood to subscribe (b = .055; p = .279). It tells us listeners are not likely to subscribe merely because influencers recommend a certain service. It could be because abundantly available information increases their confidence in their decision making, there are enough chances to try before subscribing, and people are aware of individual experience might be very much different between people regardless of the level of knowledge of various services.

TABLE 2. PLS MEASUREMENT MODEL STATISTICS

	Perceived quality		Perceived sacrifice		Perceived value		Likelihood to Subscribe	
	Weight	Loading	Weight	Loading	Weight	Loading	Weight	Loading
PERSAC3			*0.542*	*0.710*				
PERSAC4			*0.593*	*0.776*				
PQ1	*0.414*	*0.743*						
PQ2	*0.375*	*0.673*						
PQ3	*0.421*	*0.756*						
PV1					*0.437*	*0.802*		
PV3					*0.375*	*0.689*		
PV4					*0.388*	*0.713*		
WTP1							*0.395*	*0.767*
WTP3							*0.366*	*0.712*
WTP4							*0.416*	*0.809*
Cronbach's Alpha	*0.768*		*0.710*		*0.778*		*0.805*	
Composite Reliability	*0.768*		*0.712*		*0.780*		*0.807*	
AVE	*0.525*		*0.553*		*0.542*		*0.584*	

All weights and loadings are significant at the $p < .01$ level.
Model fit: SRMR = 0.040; NFI = 0.915
Reflective measures were removed based on loadings and Cronbach's Alpha

TABLE 3. LATENT VARIABLE LOADINGS AND CROSS-LOADINGS

	Perceived Quality	Perceived Value	Perceived Sacrifice	Likelihood to Subscribe	Subjective Norm
PERSAC3	*-0.269*	*-0.185*	***0.710***	*-0.173*	*-0.063*
PERSAC4	*-0.287*	*-0.217*	***0.776***	*-0.178*	*-0.008*
PQ1	***0.743***	*0.464*	*-0.270*	*0.519*	*0.313*
PQ2	***0.673***	*0.436*	*-0.153*	*0.430*	*0.370*
PQ3	***0.756***	*0.501*	*-0.377*	*0.475*	*0.289*
PV1	*0.549*	***0.802***	*-0.206*	*0.662*	*0.251*
PV3	*0.447*	***0.689***	*-0.190*	*0.584*	*0.221*
PV4	*0.422*	***0.713***	*-0.202*	*0.634*	*0.240*
SN	*0.444*	*0.322*	*-0.046*	*0.324*	***1.000***
WTP1	*0.497*	*0.652*	*-0.201*	***0.767***	*0.251*
WTP3	*0.441*	*0.652*	*-0.097*	***0.712***	*0.216*
WTP4	*0.561*	*0.650*	*-0.235*	***0.809***	*0.272*

TABLE 4. STRUCTURAL MODEL RESULTS[1,2]

Hypothesis	Path Coefficient	SD	T Statistic	P Value
Perceived Quality (PQ) → Perceived Value (PV)	*0.632*	*0.076*	*8.343*	*0.000*
Perceived Value (PV) → Likelihood to Subscribe (LS)	*0.834*	*0.043*	*19.572*	*0.000*
Perceived Sacrifice (PS) → Perceived Value (PV)	*-0.035*	*0.069*	*0.505*	*0.614*
Subjective Norm (SN) → Perceived Quality (PQ)	*0.444*	*0.064*	*6.958*	*0.000*
Subjective Norm (SN) → Likelihood to Subscribe (LS)	*0.055*	*0.051*	*1.084*	*0.279*

TABLE 5. CONTROL MODEL RESULTS

Hypothesis	Original Model				Control Model			
	Path Coeff.	SD	T Stat.	P Value	Path Coeff.	SD	T Stat.	P Value
PQ → PV	*0.632*	*0.076*	*8.343*	*0.000*	*0.630*	*0.076*	*8.282*	*0.000*
PV → LS	*0.834*	*0.043*	*19.572*	*0.000*	*0.839*	*0.045*	*18.602*	*0.000*
PS → PV	*-0.035*	*0.069*	*0.505*	*0.614*	*-0.039*	*0.068*	*0.580*	*0.562*
SN → PQ	*0.444*	*0.064*	*6.958*	*0.000*	*0.448*	*0.059*	*7.601*	*0.000*
SN → LS	*0.055*	*0.051*	*1.084*	*0.279*	*0.059*	*0.050*	*1.170*	*0.243*
Age → LS					*-0.080*	*0.046*	*1.733*	*0.084*
Gender → LS					*0.082*	*0.046*	*1.764*	*0.078*
Income → LS					*0.067*	*0.042*	*1.592*	*0.112*
Marital Status → LS					*-0.044*	*0.053*	*0.834*	*0.405*

This study controls for demographic variables including age, gender, marital status, and income. The results of the structural equation modeling test on the control models and the original model show that all path loadings, which were significant in the original model, remain significant in the control model.

Moreover all hypotheses, which were supported in the original model, are supported with the same directions in the control model. Finally, results show that none

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[1] Consumer's perceived knowledge was used as an instrumental variable to test for the endogeneity between perceived value and perceived quality. The the link between perceived knowledge and perceived value was not statistically significant, showing absence of endogeneity.

[2] Mediation test was conducted following suggestions of Zhao et al. (2010) and Hair et al. (2017). The test showed a complementary partial mediation among three variables, i.e. perceived quality, perceived value, and willingness to subscribe.

of the control variables have a significant effect on the likelihood to subscribe to a specific streaming service. Table 5 summarizes the results of this test.

V. DISCUSSION

5.1. Discussion and Implications

This paper reports nvestigates the factors that affect customer's choice in selecting a paid music streaming service. This paper explains that customer's choice is affected by several perceived elements which could be categorized as subjective and objective. Subjective factors mainly deal with the psyche of the customer, whereas objective factors are concerned with characteristics of the streaming service.

Results of this study show that perceived value acts as a mediator between quality of service and likelihood to subscribe. One major implication of this finding for practitioners is that although highest quality might be very appealing to customers, quality would always be factored in the value of the service. Therefore maintaining a balance between quality and value is crucial to convince customers to subscribe to a music streaming service.

According to the findings of this research the direct relationship between subjective norm and likelihood to subscribe is not significant whereas the indirect effect of subjective norms on the likelihood to subscribe through quality and value is supported. Main implication of this result is that although influencers could be instrumental in increasing the customer base for paid music streaming services, they would not be functional in absence of high levels of quality and value for customers.

Moreover, the results of this study supports the hypothesized positive relationship between the subjective norm and the perceived quality. This corroborates the claim of this study that perceived quality, among other factors, is influenced by the subjective norm. In other words, people whose opinion is important for the user, i.e. influencers, can change the perception of customer in perceiving a specific streaming service as high quality. → does this mean "influencers would have significant influence on customers' perceive quality toward a specific streaming service."?? This is in line with the perspective towards quality which claims that quality of a service, in part, must be judged by how well it aligns with customer needs. Obviously, customer needs, to some extent, are shaped by the social pressure or subjective norms. One main implication of this finding for practitioners is that in order to reinforce the perception of quality among users, companies must heavily invest on influencers with whom most customers relates.

The results of this study found support for the direct effect of subjective norm on the perceived quality, and failed to find support for the direct effect of subjective norm on the likelihood to subscribe. This is a very interesting result and has important implications for practitioners in the music industry. This shows that, although subjective norms are important, they do not have a direct effect on the customer's willingness to subscribe. However, if the subjective norms affect the perceived quality, that would directly, and indirectly through perceived value, affect the likelihood to subscribe. This implies that companies should choose influencers who are experts in the industry. Focusing on creating expert content through technologically savvy reviewers could be an example.

Moreover, the insignificance of the relationship between perceived sacrifice and perceived value illustrates another critical implication of this study. This result shows that the price of paid streaming services, specifically Apple Music, Spotify, and

Pandora, is not different enough to intrigue customers to switch. In presence of comparable prices, companies should focus more on changing the customers' perception about the quality of their service and worry less about promotions that focus on price reduction.

5.2. Limitations and Future Research

This research has some limitations, among which one can refer to only investigating the top three music streaming services. Although Apple Music, Spotify, and Pandora control more than half of the paid music streaming market, this results of this study would be by far more conclusive if all paid music streaming service were examined. Another shortcoming of this research is use of primary data as the only source for analysis. Although the sample size was large enough for a study of this type, the results would possess higher validity if multiple methods of data collection were used in this study. As a suggestion for future research, authors suggest using secondary information or qualitative data in conjunction with primary data to corroborate the results.

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APPENDIX A. MEASUREMENT ITEMS

Subjective Norm (Venkatesh and Davis 2000)
People who influence my choice of online services would think that I should use the service.
(1 = strongly disagree to 7 = strongly agree)
Perceived Sacrifice (Cronin et al. 2000)
The price charge to use the service is
(1 = very low to 7 = very high)
The price charge to use ______ is
(1 = very unfair to 7 = very fair)
The time required to use the service would be
(1 = very low to 7 = very high)
The effort that I must make to receive the service would be
(1 = very low to 7 = very high)
Perceived Quality (Dodds et al. 1991)
The likelihood that the service would be reliable is
(1 = very low to 7 = very high)
The workmanship of the service would be
(1 = very low to 7 = very high)
The service should be of
(1 = very poor quality to 7 = very good quality)
The likelihood that the service is dependable is
(1 = very low to 7 = very high)
The service would seem to be convenient to use
(1 = strongly disagree to 7 = strongly agree)
Perceived Value (Dodds et al. 1991)
The service is a
(1 = very poor value for the money to 7 = very good value to the money)
At the price shown the service is
(1 = very uneconomical to 7 = very economical)
The service is considered to be a good buy.
(1 = strongly disagree to 7 = strongly agree)
The price show for the service is
(1 = very acceptable to 7 = very unacceptable)
Likelihood to Subscribe (Dodds et al. 1991)
The likelihood of subscribing to the service is
(1 = very low to 7 = very high)
If I were going to subscribe to the service, I would consider subscribing to the service at the price shown.
(1 = strongly disagree to 7 = strongly agree)
At the price shown, I would consider subscribing to the service.
(1 = strongly disagree to 7 = strongly agree)
The probability that I would consider subscribing to the service is
(1 = very low to 7 = very high)